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Data-Driven Local Area Energy Framework for Modelling Domestic Heat Electrification

ABSTRACT

This paper presents a spatially referenced energy-modelling framework of the domestic building stock of a Low-Voltage(LV) electrical sub-station (i.e. Ridgeway New) in Newcastle upon Tyne for area-based heat electrification project delivery. The framework brings together several public open sources of data to generate hourly energy consumption (i.e. heat fuel and electricity) for spatially referenced individual buildings . The simulation model has been validated against Government datasets and the results are presented at three spatial resolutions: LV-area; archetype; and individual building. Our discussion focuses on peak household energy demands highlighting that peak hourly ratios are significantly higher than expected. We also comment on the models' assumptions and uncertainties.

INTRODUCTION

Within urban energy transitions, the decarbonisation of heat is arguably the biggest challenge facing European Union (EU) (Europe 2017) and UK energy policy over the next few decades (OFGEM 2016). Currently, in the UK, the aggregate heat peak demand (at roughly 300 GW) is approximately 5 times greater than that for electricity (OFGEM 2016). On the supply side, on the other hand, heat mainly comes from burning natural gas (over 70% for domestic, industry and service sectors) (OFGEM 2016).

Motivation, context, and ongoing outcomes

Newcastle City Council (NCC) is a UK local authority committed to energy and carbon emission reduction policies via area-based carbon reduction strategies (ETI 2018), (Shackley, P. Fleming, and Bulkeley 2002, p. 48) and with heating accounting for over 60% of total demand for energy in Newcastle, decarbonising heat, domestic heat in particular, is a critical component of achieving the city's decarbonisation goals.

Newcastle City Council (NCC) is a national path-finder in developing a local area energy plan utilising a whole-system analysis approach known as Energy Path Networks (EPN) (ETI 2017). Specifically, EPN analysis has highlighted under multiple scenarios that electrification of heat (e.g. using heat pump based solutions) is often the optimal decarbonisation solution for a significant proportion of Newcastle's housing stock (ETI 2018).

Our recent study (Calderón et al. 2019) showed that the electrification of heat at city-scale will have a substantial impact on the local electrical grid infrastructure (i.e. 59-95% additional (winter) peak household electricity demand); emission savings will be achieved with all electrification options studied; and that at a Low-Voltage(LV) electrical substation was the appropriate spatial scale for identifying neighbourhoods where local heating electrification was the only possibility for domestic heat decarbonation solution. Figure 1 shows one of the identified areas: Ridgeway New. In this figure (Fig. 1), the light colour dots represent individual houses (i.e. 228 in total) associated to the LV substation (i.e. the electric tower icon). In this paper, we use Ridgeway New as our case study area. However, to move from neighbourhood identification to project delivery will require developing integrated modelling approaches to cope with forthcoming energy system design challenges at LV scale such as increasing electric mobility, distributed generation and storage, as well as smart grids and controls (Calderón et al. 2019). For example, at a building level, this approach will need a representative sample of domestic dwellings (see Fig. 1) over short time intervals in order to capture transient electrical demands and their interaction with the more damped (but seasonal) heating demand patterns. This paper focuses on the building level and presents an analytical spatially referenced (i.e. UPRN) domestic building energy modelling framework at a LV electricity sub-station spatial scale for area-based heat electrification project delivery. In this article, we first review current modelling practice to contextualise our simulation framework. The developed simulation framework is then presented. The results show the model validation against UK Government datasets and are presented at three spatial resolutions: LV-area; archetype; and individual building. In the discussion section, we elaborate the challenges faced when developing this type of models and future areas of work.

CURRENT PRACTICE

General excellent comprehensive and systematic reviews on modelling and simulation of buildings energy systems such as (Harish and Kumar 2016) as well as with a UK focus (Hall and Buckley 2016) have been already undertaken. However, there are significantly less modelling tools which are designed to produce accurate energy simulation results at high spatial and temporal resolutions needed for this study (i.e. at LV scale and hourly). Figure 2 presents existing tools (CitySim(Robinson et al. 2009);Simstadt(Nouvel et al. 2015); UBEM(Reinhart and Davila 2016); CityBES (Hong et al. 2016); CEA(Fonseca

Figure 1: Areal and schematic view of domestic housing stock fed by one LV substation. As per real data provided by the Newcastle City Council.

et al. 2016)) and analyses them by urban system boundary, building type, building grouping, simulation type, simulation time-step, thermal zones, validation and data. Of the reviewed models, only CEA model has been designed with a sufficiently high spatial resolution for the purpose of our study (i.e. micro-neighbourhood level). However, the CEA tool relies on archetypes (Fonseca et al. 2016) for building characterisation as opposed to uniquely and spatially defined (i.e. UPRN) buildings. Similarly, assigning data at individual urban building level is either not clearly specified or relies mainly on disaggregation assumptions (Robinson et al. 2009) (Hong et al. 2016).

In the next section, the developed spatially and uniquely referenced (i.e. UPRN) domestic building energy modelling framework and the use data sources are presented.

SIMULATION FRAMEWORK

The presented simulation model is able to generate hourly energy consumption (i.e. fuel and electricity) for spatially referenced individual buildings. The simulation has been developed following Reinhart et al.'s (Reinhart and Davila 2016) approach and implemented in Rhino Grasshopper®. Geometrical and non-geometrical individual building level data as well as weather data are fed into Energy Plus so as to produce hourly heat fuel and electricity consumption profiles for individual buildings (see Figure 3).

Data Sources

Table 1 summarises the collected urban data by sub-categories: building stock geometric data, building stock non-geometric data, and weather data.

Model Data Verification

GIS desktop "ground-truthing" of the selected area was carried out to empirically test building geometry and property data matching procedure. Common geometry parameters can be found in the TOID (TOpographic IDentifier) dataset and the ABP (AddressBase Premium) dataset. Namely, total floor area and building height. After these two datasets were brought together, only 0.02% (6 out of 228) of the buildings had a mismatch of geometry data. These were then crossed checked on Google Earth Pro®(Google Earth Pro, 2018), and an estimate of the mistaken building heights is drawn. Google Street View®was used to spot whether building classifications correspond to the 'truth' on the ground. Parameters verified included window to wall ratios, property types and buildings' heights.

Building geometric data: 2.5D model

EDINA Digimap shapefiles and UPRN XML building heights data were linked to a TOID number and were used to automatically generate 2.5D massing flat roof models suitable for energy simulation (see Figure 4). All non-energy consuming building units and dwellings that were not featured in one of the matched datasets (ABP and TOID) were excluded. As a result, a 228 domestic 2.5D buildings, each identifiable by their Unique Property Reference Number (UPRN), LV model was created. Each building was defined by a single thermal zone.

Energy Efficiency

Building fabric energy efficiency measures were obtained from Energy Performance Certificate (EPC) (Goverment. 2019) data which is uniquely linked to the building UPRN. An EPC provides building's fabric description (wall, roof and floor) and glazing characteristics (single, double and triple glazing). A typical envelope U-value and glazing G-value were assigned the each of the building envelope components based on the building's EPC fabric description.

Energy Systems

The main heating fuel and system(s) were identified from the EPC data (Goverment. 2019). Example systems include Boiler system with radiators, storage radiators, warm air system and room heater. Similarly, for DHW options were identified with central heating, dedicated boiler or electric immersion heater. For each of the systems a system efficiency was assigned accordingly and only gas heating fuel options were considered for this study. As a result, simulated electricity energy consumptions relate only to lighting and electric equipment.

Model description			Urban Boundary			Blding. Group		Simul. Type		Time-step			Thermal zon.		Validation		Data
Simulation tool	Year	Software Platform	City(Macro)	Discric(Meso)	Neighbourhood (Micro)	Building Archetype	Individual Building	Steady state	Dynamic	Yearly	Monthly	Hourly	Single zone	Multiple zones	Sensitivity Analysis	Output Validation	Open source
CitySim	2006	Java		■		■			■			■		■		■	
SimStadt	2015	CityGML		■		■		■			■		■			■	
UBEM	2015	Rhino/GIS	■			■			■			■	■			■	
CityBES	2016	Open Studio	■				■		■			■			■		
CEA	2016	Python/GIS			■	■			■			■	■		■	■	■

Figure 2: Urban Energy Modelling approaches review.

Table 1: Data subcategories, input variable, sources and year

Subcategories	Model input variables	Primary Data Sets	Year
Geometrical	Building location and 2D footprint	EDINA Digimap (EDINA 2018)	2018
	Height	OS AddressBase Premium (OS 2018)	2015
	UPRN, Type, Age, Total Floor area	OS AddressBase Premium (OS 2018)	2015
	Envelope characteristics	EPC data (MHCLG 2108)	Variable
Non-Geometrical	Domestic appliances user profiles	UK housing energy fact file (Palmer and Cooper 2013)	2013
	Occupancy data per household	Street Check (SC 2018)	2018
	Household employment	Nomis statistics (ONS 2018)	2011
Weather	Local data	PROMETHEUS (PROMETHEUS 2011)	2011

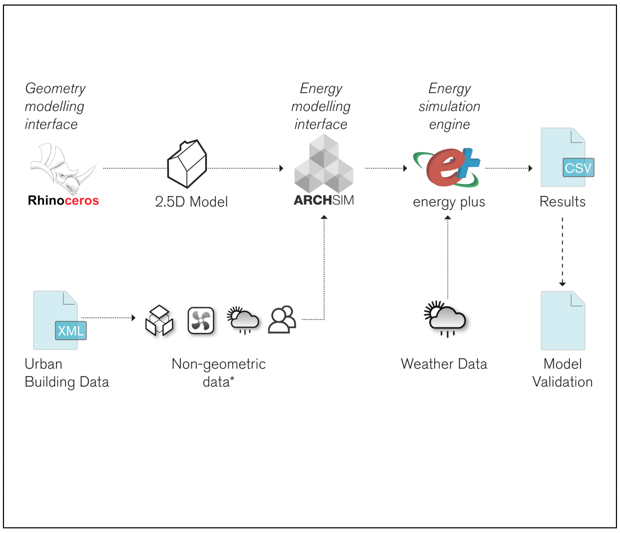

Figure 3: Simulation framework overview

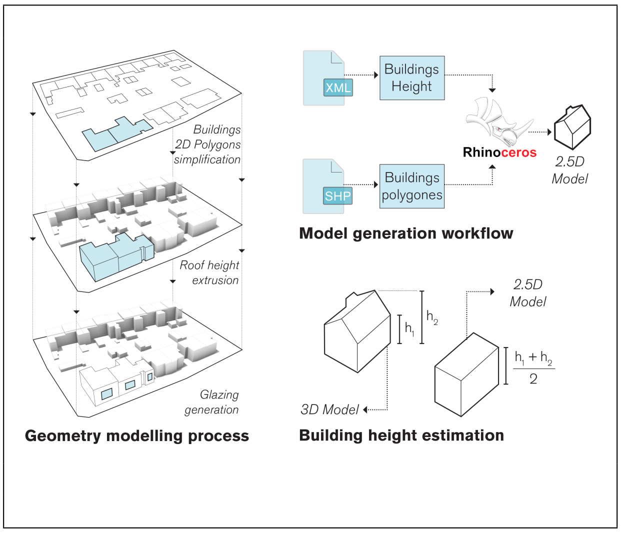

Figure 4: 2.5D model: building's height

Building non-geometric data: Household Characteristics

Household occupancy count and behaviour, and socio-demographic information were obtained at an Output Area (OA)/ postcode level, from several open-source data (SC 2018) (ONS 2018). These data streams were joined, aggregated and assigned per UPRN and the following model assumptions were made:

- Zone loads. Whenever occupant number is not available an estimated people density figure (person/m^2) was assigned based on (Palmer and Cooper 2013).
- The heating setpoint schedule was set to 18:00 to 06:00 or 24 hours based on the employment status, and household occupation collected data (Palmer and Cooper 2013).
- Domestic appliances use profiles was set for all domestic dwellings as per (Palmer and Cooper 2013) with constant equipment power density ($W\,m^{-2}$) and lighting power density ($W\,m^{-2}$).
- Domestic Hot Water (DHW) demand was assigned per capita per UPRN m^3 h/person as per (Chmielewska, Szulgowska-Zgrzywa, and Danielewicz 2017)

RESULTS

The simulation outputs comprise of four estimated energy uses: space heating, electrical equipment loads, lighting loads, and domestic hot water. Those uses can be grouped between electricity demand and heat fuel demand.

For validation purposes, the simulated energy output were compared with empirical data provided by the National Energy Efficiency Data Framework (NEED) (BEIS 2019). The NEED data provides energy consumptions by both house type and by floor area band by each UK local authority.

Validation

Table 2: Median annual heat fuel and electricity consumption comparison.

	DEM-LV kWh	**NEED** kWh	**Difference** %
Fuel	10,966	12,740	-14
Electricity	2,411	2689	-10

In general, the results compare favourably with a tendency for the present work estimated electricity consumption to be higher than NEED at floor area basis but lower at property type level. On the other hand, NEED data show consistently higher gas consumption than the present work shows. The simulation recorded output provides confidence in the model's calculation, with an overall error percentage of 12% . This is broken down as follows: 10% for electricity consumption and 14% for heat fuel consumption (see Table 2), always being lower than the NEED reference. As the overarching purpose of NEED is to monitor progress on energy efficiency improvement measures to the UK housing stock. It might, therefore, be anticipated that the NEED data will be biased towards houses with insulation upgrades and NEED estimations, as a result, should be higher.

Floor area bands based comparison

To compare results on a floor area band basis with equal weighting, it is appropriate to consider a uniform range of floor areas to comply with NEED data categorisation. The simulated building stock within Ridgeway new neighbourhood were aggregated per NEED floor area bands as such: 50 or less, 51 to 100, 101 to 150, 151 to 200 and over 200 m^2. Table 7 shows the number of dwellings by floor area band within the sample. Energy consumption results per floor area band, were then averaged and compared with NEED data energy estimates (see Tables 3 and 4).

Table 3: Electricity consumption comparison by floor area bands in kWh *between NEED and present work*

Floor band (m^2)	**DEM-LV** (kWh)	**NEED** (kWh)	**Difference** %
50 or less	1,182	1,936	-39
51 to 100	2,230	2,508	-12
101 to 150	3,321	3,118	6
150 to 200	5,947	3,859	54
Over 200	6,740	5,103	32

Table 4: Heat fuel consumption comparison by floor area bands in kWh *between NEED and present work*

Floor band (m^2)	**DEM-LV** (kWh)	**NEED** (kWh)	**Difference** %
50 or less	6,255	7,547	-18
51 to 100	11,296	11,408	-1
101 to 150	13,928	16,252	-15
150 to 200	14,207	22,841	-38
Over 200	24,050	29,956	-20

House type based comparison

To compare results on a property type basis with equal weighting, it is appropriate to consider similar categorisation as NEED data. The simulated building stock within Ridgeway new neighbourhood were aggregated per property type as such: Detached, semi-detached, end-terrace, mid-terrace, bungalow, converted flat, and purpose-built flat. The last three categories do not exist with the Ridgway new neighbourhood, thus were excluded in the comparison analysis. Table 7 shows the number of dwellings by house type within the sample. Energy consumption results were then averaged per property type and compared with NEED data energy (see Tables 5 and 6).

Table 5: Electricity consumption comparison by house type in kWh *between NEED and present work*

House Type	**DEM-LV** (kWh)	**NEED** (kWh)	**Difference** %
Detached	3,685	3,599	2
Semi-Detached	2,220	2,996	-26
End-Terrace	2,334	2,762	-16
Mid-Terrace	2,307	2,847	-19

Table 6: Heat fuel consumption comparison by house type in kWh *between NEED and present work*

House Type	**DEM-LV** (kWh)	**NEED** (kWh)	**Difference** %
Detached	13,390	17,843	-25
Semi-Detached	11,862	15,248	-23
End-Terrace	9,337	12,251	-24
Mid-Terrace	9,275	12,521	-26

Fuel and electricity domestic building stock profiles

This section presents the results of the developed modelling framework. The results are presented at three spatial resolutions: LV-area; archetype; and individual building. Energy consumption is presented as heat fuel and electricity consumption. Fuel represents space heating and domestic hot water whereas electricity represents lighting and electrical appliances.

LV area

Figure 5 shows the average heat fuel and electricity energy consumption for all the 228 domestic dwellings in Ridgway (New) with a w inter (January) heat peak of 1828 kWh and a through of 177 kWh in August. Electricity consumption has a flatter profile with winter (January) peak of 323 kWh and a through of 109 kWh in August.
As understanding peak energy consumption is critical for heat electrification planning in Ridgeway (new), the rest of our analysis focuses on January (peak month) at hourly temporal resolutions. Figure 6 shows average hourly electricity and heat fuel consumptions throughout the month of January for all 228 dwellings in Ridgeway (New) with heat peak of 2538 kWh between 22:00 and 6:00 hours and an electricity peak of 0.970 kWh between 17:00 and 20:00 hours.

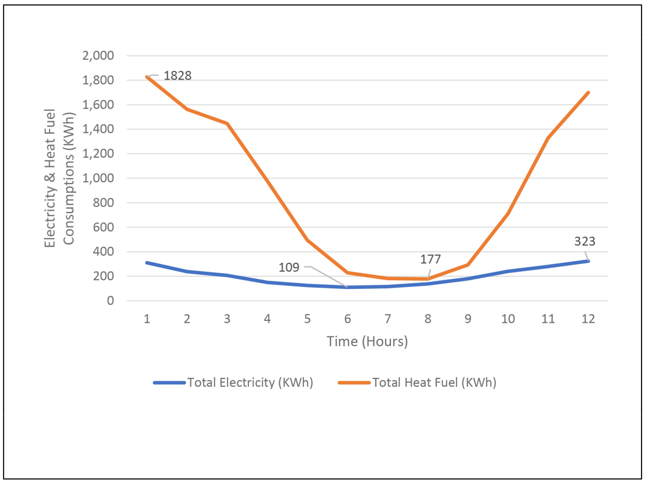

Figure 5: LV area monthly average total electricity and heat fuel consumption in kWh

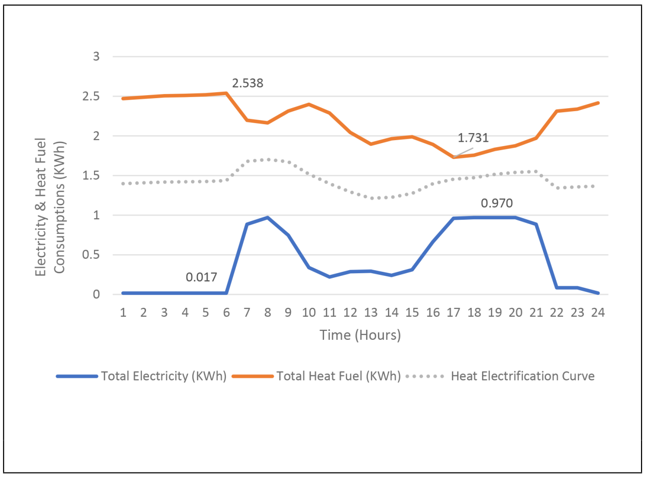

Figure 6: LV area January hourly average total electricity and heat fuel consumption in kWh

Archetype

Table 7 illustrates the archetypes present in Ridgeway New by age band, house type, and floor area band. For our archetype analysis, a 1914-1944 semi-detached 51 m^2 to 100 m^2 with 71 dwellings was selected. This archetype is not only the second largest but semi-detached houses have reasonable gardens which are suitable for building centric heat electrification solutions such as ground source heat pumps.

Figure 7 shows average hourly electricity and heat fuel consumptions throughout the month of January for the selected archetype with heat peak of 2648 kWh and an electricity peak of 0.876 kWh.

Table 7: Archetypes number, indicated between parenthesis, in Ridgeway (new) by age band, house type, and floor area band.

Age band	House type	Floor area band
1914-1944(219)	Detached (14)	51 m^2 to 100 m^2 (7)
		101 m^2 to 150 m^2 (5)
		151 m^2 to 200 m^2 (2)
	Semi-detached (85)	50 m^2 or less (6)
		51 m^2 to 100 m^2 (71)
		101 m^2 to 150 m^2 (7)
		151 m^2 to 200 m^2 (1)
	Mid-Terrace (85)	51 m^2 to 100 m^2 (83)
		101 m^2 to 150 m^2 (2)
	End-Terrace (35)	51 m^2 to 100 m^2 (31)
		101 m^2 to 150 m^2 (3)
		151 m^2 to 200 m^2 (1)
1945-1944 (7)	Detached (7)	101 m^2 to 150 m^2 (6)
		Over 200 m^2 (1)
1965-1979 (1)	Detached (1)	Over 200 m^2 (1)
1980-present (1)	Semi-detached (1)	51 m^2 to 100 m^2 (1)

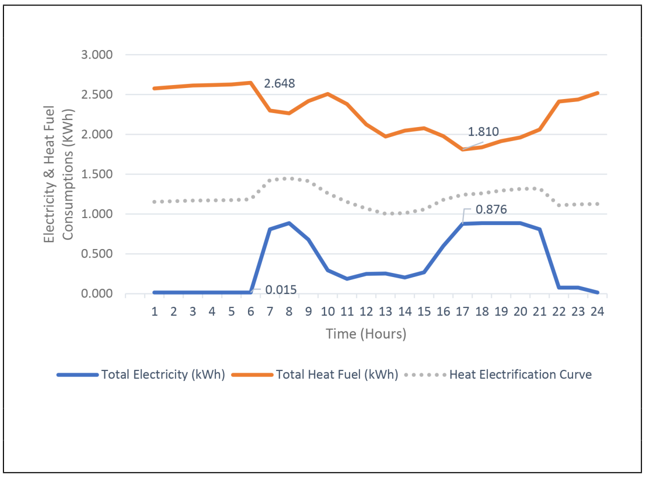

Figure 7: Archetype January average hourly average total electricity and heat fuel consumption in kWh

Individual dwelling

Figure 8 shows average hourly electricity and heat fuel consumptions throughout the month of January for an individual dwelling (UPRN 4510044758) pertaining to the selected archetype with heat peak of 3440 kWh and an electricity peak of 0.988 kWh. Figure 9 shows average hourly electricity and heat fuel consumptions throughout the month of January for an individual dwelling (UPRN 4510044758) split further into heating and domestic hot water and lighting and electrical appliances.

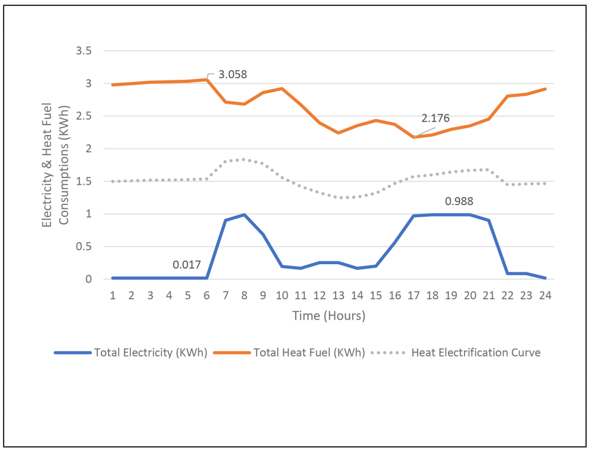

Figure 8: Dwelling January hourly average total electricity and heat fuel consumption kWh

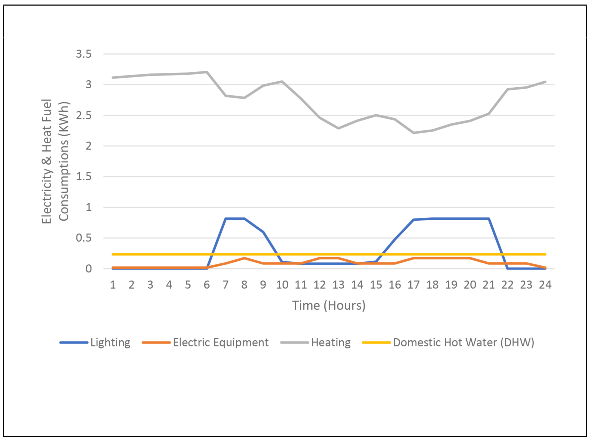

Figure 9: Dwelling January hourly split total electricity and heat fuel consumption in kWh

DISCUSSION

Validation and results

In general, as shown in Table 2, the validation results compare well with NEED. Furthermore, a significant proportion, 69%, of the estimated housing stock has a floor area band of 51 m^2 to 100 m^2. For this segment, our heat fuel and electricity validation results show higher alignment with NEED, -1% and -12% respectively (see Tables 4) , 3). There are however some caveats. IA significant increase in the percentage of error was observed in the floor area bands classification for both electricity and heat fuel consumptions. High percentages of errors (%=Simulated-NEED data/ NEED data) were observed at bands 50 or less (-17% for heat fuel, -39% for electricity), 151 to 200 (-38% for heat fuel, 54% for electricity) and over 200 m^2 (-20% for gas, 32% for electricity). The results mismatch could be explained by the few numbers of the estimated domestic houses which fall under this category. For instance, out of the 228 houses, 7 fall under the 50 or less category, 3 fall under the 151-200, and another 3 fall under the over 200 m^2category. Whereas for NEED data, 11,932 falls under the 50 or less category, 5,464 fall under the 151-200, and 2,082 fall under the over 200 m^2.

Temporal resolution

Understanding peak household energy demands is critical in heat electrification planning as heat loads will be transferred to the electrical local electricity network at LV scale. Our results highlight the significance of temporal resolutions to ascertaining peak loads. For instance, the 228 domestic dwellings in Ridgway (New) have a winter montly (January) heat peak 5.65 times higher than the electricity peak (i.e. 1828 kWh heat January montly peak vs a 323 kWh electricy peak in January see Figure 5). From an hourly perspective, Table 8 provides a summary which clearly shows the impact of transferring heat loads at peak "hourly" time will be much greater (i.e. up to 3,481 times higher than the electricity).

Table 8: Median annual heat fuel and electricity consumption comparison.

	Heat Peak (kWh)	**Electricity Peak** (kWh)	**Times** (x)
LV	2,538	0.970	2,616
Archetype	2,648	0.826	3,205
Building	3,440	0.988	3,481

A 5.65 times ratio is consistent with existing literature. For example, (McLean et al. 2016) notes that at UK national level, based on energy output, peak gas demand for heat at 300GW is: "5 times greater than the level would be if it were spread evenly over the days and seasons; 12 times the summer maximum; between 5 and 6 times the current peak in the electricity system" (McLean et al. 2016, p. 20). However, peak hourly ratio are significantly higher and those should be fully explored with detailed demand calculation modelling such as After Diversity Maximum Demand (ADMD). ADMD has been used (Barteczko-Hibbert 2015). This approach focuses on the diversity of large numbers of electrical consumers or 'customers'. ADMD is used in the design of distribution networks where demand is aggregated over a large number of customers and represents the mean of peak demands for a group of customers. ADMD is the maximum demand observed for a group of customers over typically one year time. (CLNR 2015).

Spatial resolution

Whilst LV area modelling gives indication about electricity network capacity. The archetype categorisation allows for more localised interventions. Table 8 seconds the thinking that archetypes are a good approximation for planning heat electrification at LV scale as they capture the key factors which affect the heat/electricity peak ratios. However, the modelling assumptions behind those key factors are far from certain and our thoughts are outlined in the next section.

Uncertainties

Our work demonstrates that high temporal (hourly) and spatial (individual building) estimation of LV area is technically possible. Higher temporal-spatial resolutions are important in heat electrification area planning at LV scale as it enables the estimation of peak shaving and shifting solutions with measures such as thermal storage, demand side response, or time-of-use tariffs. However, uncertainty when developing these type of models is an important and pervasive aspect. Whilst a full uncertainty analysis of our model is outside of the scope of this paper, table 9 provides a description of location (sources), level and issues of uncertainty. The table builds upon the taxonomy presented in our previous work domestic energy end-use demand estimation work at sub-city level (Calderón et al. 2015).

Table 9 shows that there severe modelling uncertainties around building fabric and energy systems (e.g. infiltration rates), and household characteristics (e.g. occupant behaviour). For instance, general occupant behaviour assumptions have been based on regional statistics, our research show that for high temporal resolution modelling (i.e. 1 hour or less) individual household characteristics such as occupants count, energy use profiles, employment status and jobs have a very significant direct effect on the pattern of use. This coincides with current thinking (Paone and Bacher 2018). Furthermore, the presented simulation has limitations due to the simplifications made. The most significant are: i) model simplification modelled at 2.5 D by using the plan footprint and the average building height (disregarding the roof shape); and ii) buildings have been simulated as singular thermal zones. The study would have benefited from a more comprehensive zoning of buildings per floor or even per floorplan.

Next steps

Our work shows that this type of high spatial-temporal resolution models are needed and valuable for planning area-based heat electrification. However, exploring fully the uncertainties surrounding these type of models is a necessary step. Similarly, better capturing of the network characteristics so as to assess the impact of domestic heating electrification on the network capacity and cost is necessary. This should be coupled with adequate electricity network modelling such as the outlined ADMD.

Table 9: Model uncertainties: location, level, and issues

Location	Level	Issues	Description
Context	Boundaries	Modifiable area unit	LV network analysis scale.
Model	DEM-LV	Building fabric and systems data	EPC derived data: building height, fabric, infiltration rate, heating system.
		Building energy generation	No electricity generation was assumed.
		Thermal modelling	The number of thermal zones has been simplified to one per building.
		Socio-economic	Household characteristics were captured at an aggregated zonal area then applied to the individual buildings. Occupant behaviour represented by a standard daily heating and electricity schedules.
		Urban Landscape	Site topography and surface characteristics were not modelled.
		Microclimate	A typical reference year regional weather data has been assigned.
Validation	BEIS Data	NEED	Biased towards houses with insulation upgrades. Dwellings samples unevenly distributed per floor area and house type classifications.

CONCLUSION

This paper has presented a spatially referenced energy-modelling framework of the domestic building stock of a LV electrical sub-station (i.e. Ridgeway New) in Newcastle upon Tyne for area-based heat electrification project delivery. Open sources of data were used to generate hourly energy consumption (i.e. heat fuel and electricity) for spatially referenced individual buildings . The simulation model has been validated against Government datasets and the results are presented at three spatial resolutions: LV-area; archetype; and individual building. Our results highlight the significance of temporal resolutions to ascertaining peak loads. Particularly, the results suggest that peak hourly ratio are significantly higher than peak monthly ratio. As a result, peak hourly ratio should be fully explored with detailed demand calculation modelling such as After Diversity Maximum Demand (ADMD).

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